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A spatial model for the instantaneous estimation of wind power at a large number of unobserved sites

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Abstract

We propose a hierarchical Bayesian spatial model to obtain predictive densities of wind power at a set of un-monitored locations. The model consists of a mixture of Gamma density for the non-zero values and degenerated distributions at zero. The spatial dependence is described through a common Gaussian random field with a Matérn covariance. For inference and prediction, we use the GMRF-SPDE approximation implemented in the R-INLA package. We showcase the method outlined here on data for 336 wind farms located in Denmark. We test the predictions derived from our method with model-diagnostic tools and show that it is calibrated.

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Keywords: Wind power prediction; Bayesian hierarchical models; integrated nested Laplace approximation

1. Introduction

Worldwide, wind power is rapidly increasing its representation on newly installed electricity capacity. Denmark has the largest proportion of wind energy capacity compared to the size of the electricity consumption; it represented 32.7% of the total energy consumption in 2013 and increased to 39.1% in 2014. The heavy investments that have been placed in this area ask for advanced forecast methodologies to address issues related to intermittency and limited predictability of power generation. Increasing the accuracy of wind energy forecasts is not only important for efficient management of power systems[1], but also helps increasing the revenues from electricity market with the optimization of bidding strategies[2].

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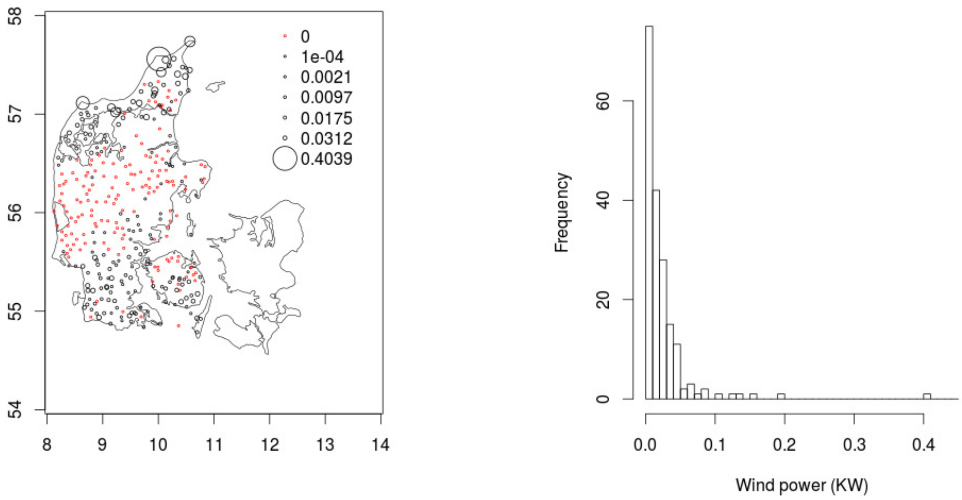

Fig. 1: Map and histogram of the normalized wind power that is greater than zero at 336 stations in Denmark at a specific daytime of 2009.

The conventional geostatistical methodology, kriging, considers the stochastic spatial variation in the data as normally distributed. However, wind power generation is clearly not Gaussian and its intermittency yields a probability mass at zero. Departure from normality can easily be handled but comes at a computational cost[3]. Here we use integrated nested Laplace approximations (INLA)[4] as an alternative to MCMC methods, which opens the door to near real-time applications. We showcase our approach on a data set consisting of average power measurements with a 15 minutes time step for 336 wind farms in Western Denmark.

2. Hierarchical model for wind power generation

We use a hierarchical model that considers wind power generation occurrence first, and then model nonzero wind power conditional on its occurrence. Our approach is based on a mixture of distributions with a shared spatial component represented by a Gaussian random field with Matérn covariance function. The first distribution is a Bernoulli with binary response for the occurrence of wind power; the second distribution is a Gamma density for the nonzero values, which represents the amount of wind power generated. The spatial statistical model underlying our method consists of a jointly model arising from two distinct stochastic processes: the occurrence and the amount of wind power. The model for each variable is given by Equation (1) and Equation (2).

$$Z_i \sim Bernoulli(p_i) \quad \text{with} \quad \log\left(\frac{p_i}{1-p_i}\right) = \alpha_z + x_i, \quad i = 1,\ldots,336 \tag{1}$$

$$Y_i \sim Gamma(a_i, b_i) \ \text{with} \ \log(\mu_i) = \alpha_y + \beta x_i, \quad i = 1,\ldots,336 \tag{2}$$

where $E(Y_i) = \mu_i = \frac{a_i}{b_i}$ and $Var(Y_i) = \frac{a_i}{b_i^2} = \frac{\mu^2}{\phi}$, where ϕ is the precision parameter. The spatial correlation is captured by x_i, which is a Gaussian random field shared by both distributions. The Gaussian field has a covariance function belonging to the Matérn family and given by Equation (3)

$$r(s,s') = \frac{\sigma^2}{4\pi\kappa^2}(\kappa \| s-s' \|) K_1(\kappa \| s-s' \|) \tag{3}$$

At Equation (3), K_1 is the modified Bessel function of second kind, order 1. Note that, κ can be used to select the range and then σ to achieve the desired marginal variance. It follows that the vector of parameters to be estimated is given by $\theta = (\alpha_z, \alpha_y, \beta, \phi, \sigma, \kappa)$.

3. Illustration of the method and discussion

We use our hierarchical model to evaluate the accuracy of out-of-sample predictions and compare the performance with two benchmark methods: Ordinary Kriging, which is based on the interpolation of the normalized wind power data for which the interpolated values are modeled by a Gaussian process with a Matérn covariance, and Kernel smoothing, used to obtain a probability density function from a normal kernel based on the closest 20 stations.

We evaluate the predictive performance using leave-one-out cross-validation with *reliability* and *sharpness* diagrams. Reliability represents the ability of the forecasting system to match the observation frequencies. Ideally, the nominal rates and the observed frequencies would be the same, resulting in points aligning with the diagonal. However, a reliable forecast is not useful if it is not informative. The sharpness diagram gives an indication of the spread of the predictive distributions. It is measured by the average interval size in the case of predictive intervals, which should be as tight as possible for a sharp forecast[5].

The plots on top of Figure 2 show a comparison between the hierarchical model and the benchmark methods of the reliability diagram together with the respective consistency bars (left) and sharpness (right), for the wind power measurements greater than zero. The plots on the bottom of Figure 2 show the same type of diagrams for the probability of wind power >0 given by our hierarchical model. The expected fluctuations in the observed frequencies are plotted as consistency bars using the binomial density. For the bottom left plot, the bars were calculated using consistency resampling as in [6].

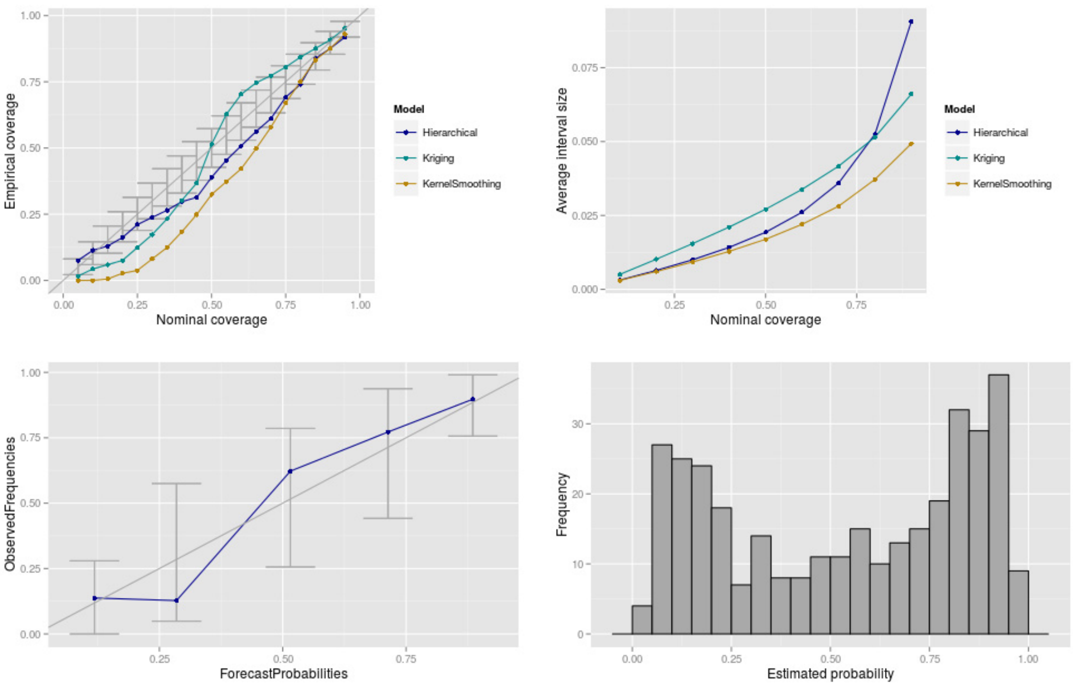

Fig. 2: Reliability diagrams with respective consistency bars (left column) and sharpness (right column) for the amount of generated wind power greater than zero (top row) and for the probability of wind power occurrence (bottom row).

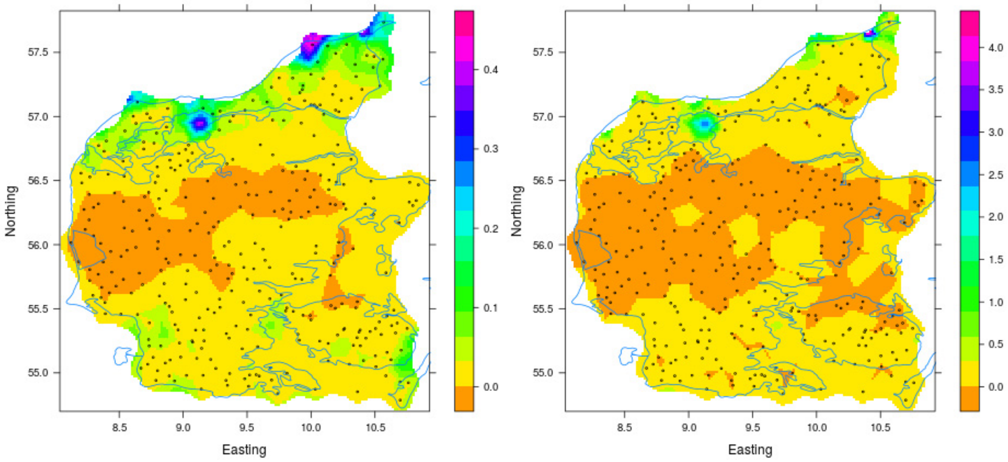

Fig. 3: Predicted mean (left) and standard deviation (right) of wind power. The black dots are the locations of the wind farms.

From the top plot of Figure 2, we can see that the hierarchical model seems to perform best, with most of its quantiles within the consistency bars while having interval sizes close to the benchmark methods, except for the 0.95 quantile. For the probability of wind power occurrence, as we can see from the bottom plot of the same figure, the empirical frequencies always fall within the consistency bars, implying that we don't reject the hypothesis that the system is calibrated. The bar plot on the bottom right indicates that the probability is sharp, since in many occasions the predicted probability is close to the extreme values 0 or 1. Figure 3 shows the map of the Western part of Denmark together with the predicted wind power produced and the standard deviation of the predictions.

4. Summary and Perspectives

Inference and prediction under complex hierarchical spatial models well suited to wind data can be implemented seamlessly under the GMRF-SPDE approximation implemented in the R-INLA package. It provides not only point estimates but also predictive densities and maps of intermittence. The next step of this study will be to carry out a validation of the approach outlined here on a full year of wind power record with a 15 min time interval in Western Denmark. The R code used to perform prediction is available from http://www2.imm.dtu.dk/~amle/ for future reference and reproducibility.

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